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A REVIEW ON IMAGE RECOGNITION OF BRAIN TUMOR USING MRI SCANS

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ABSTRACT

Brain tumors, characterized by irregular cell growth within the brain, pose considerable health risks. Timely detection is crucial for optimizing treatment effectiveness and improving overall patient survival rates. Magnetic Resonance Imaging (MRI), widely employed for diagnostics, furnishes intricate images delineating the brain's structure and operations. Nonetheless, the manual identification and segmentation of brain tumors from MRI images represent intricate tasks, necessitating the proficiency of highly skilled professionals. In recent years, research endeavors have predominantly concentrated on conventional machine learning approaches for diagnosing brain tumors. Nevertheless, a discernible paradigm shift is observed towards the exploration of deep learning techniques, driven by their heightened capabilities and enhanced accuracy. This review paper endeavors to expound upon the noteworthy achievements within the realm of brain tumor diagnosis processes.

Keywords: Segmentation, Pre-Processing, Classification.

1. INTRODUCTION

Currently, brain tumors have become a worldwide problem, contributing significantly to mortality and disability. According to the World Health Organization, there are 120 different types of brain tumors, which include both primary and secondary forms. A brain tumor is an abnormal proliferation of cells in the brain, lacking any physiological function. These tumors can either originate in brain tissue (primary tumors) or result from the migration of cancer from other parts of the body (secondary tumors). Analysis and treatment of brain tumors depends on a variety of factors, including type, location, size, grade, age, and overall health.[1] Tumors not only affect the size of the brain, but also cause swelling, leading to abnormal neurological symptoms.Primary tumors develop in the brain, while secondary tumors arise from the spread of cancer cells originating elsewhere. Brain tumor detection and treatment strategies depend on a comprehensive assessment of these factors. Magnetic resonance imaging (MRI), a non-invasive imaging technique, plays a key role in diagnosis by providing detailed information about the anatomy, physiology and pathology of the brain. As a diagnostic test, MRI scans use magnets and radio waves to create highly detailed images of various structures and organs in the body, including the brain. Despite the invaluable insights provided by MRI scans, the brain tumors detection from these images manual poses significant challenges. Factors such as image noise, blur, and heterogeneity, reflecting the existence of subpopulations of cells with distinct genotypes and phenotypes, add to the complexity of the detection process. In solving these problems, image processing techniques that involve the manipulation, analysis and interpretation of digital images come into play. Techniques such as enhancement, filtering, segmentation, classification and visualization can be strategically applied to MRI images. Not only does it improve image quality, it also helps in the accurate and efficient detection of brain tumors, increasing diagnostic accuracy and contributing to improved patient outcomes.

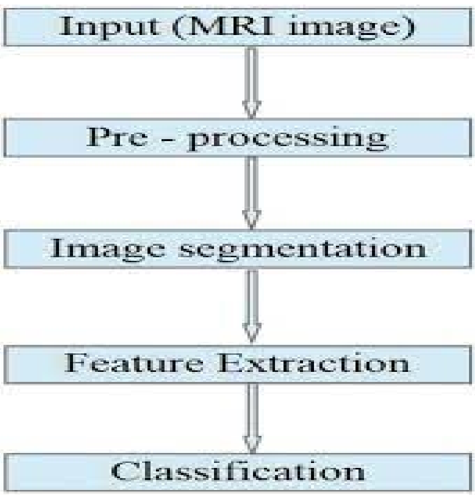

Fig. 1 processing steps :

1.1 Segmentation: The process of dividing MRI images into regions with similar characteristics is essential for obtaining accurate information. This is accomplished through various techniques such as thresholding, region growing, clustering, watershed, and edge detection. Segmentation ensures that the processed image is broken down into several segments, making it easier to analyse.

1.2 Pre-Processing: The initial step in image processing involves actions like opening, closing, smoothing, sharpening, and intensity normalization. This crucial step improves the quality of images, allowing them to be resized according to specific pixel requirements. Additionally, tumor segmentation can be achieved using a KNN approach, incorporating a straightforward feature vector combined with conditional random fields.

1.3 Optimization: Optimization plays a crucial role in enhancing the accuracy and robustness of the segmentation process.

1.4 Feature Extraction: Extracting relevant information from segmented MRI images is a subsequent step, providing valuable insights for further analysis.

2. TUMOR DETECTION

The identification of the presence or absence of a tumor in the brain is crucial for early diagnosis and effective treatment of patients, utilizing datasets or databases of MRI images. Various techniques, including SVM, KNN, CNN, and ANN, can be employed for the detection of brain tumors through MRI images. Considering the dissimilarity between the tumor center and the expected region, predicting the probability of encountering each pixel during the investigation process increases the resolution between pixels in the three tumor classes. In essence, knowledge of the expected center's location contributes to more accurate tumor detection.The below figure(fig.1)shows the steps involved in tumor detection using image processing.

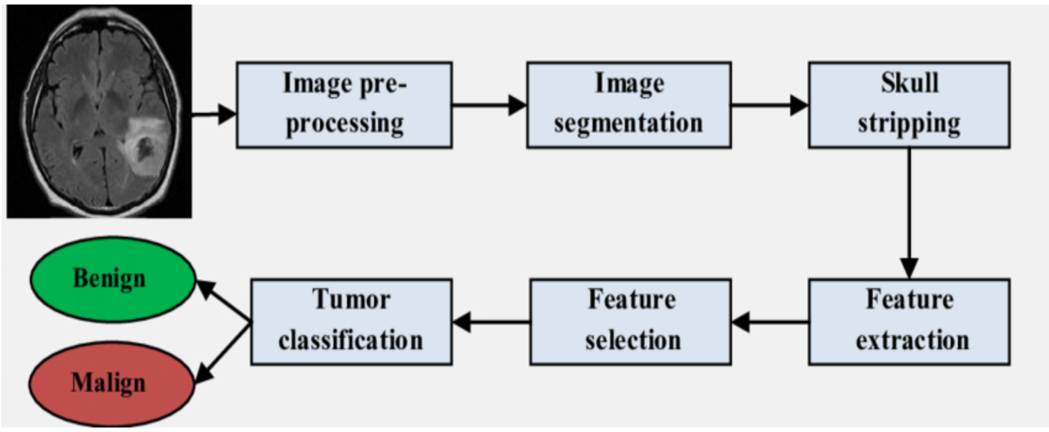

Fig.2

The above figure(fig.1)shows the steps involved in tumor detection using image processing.

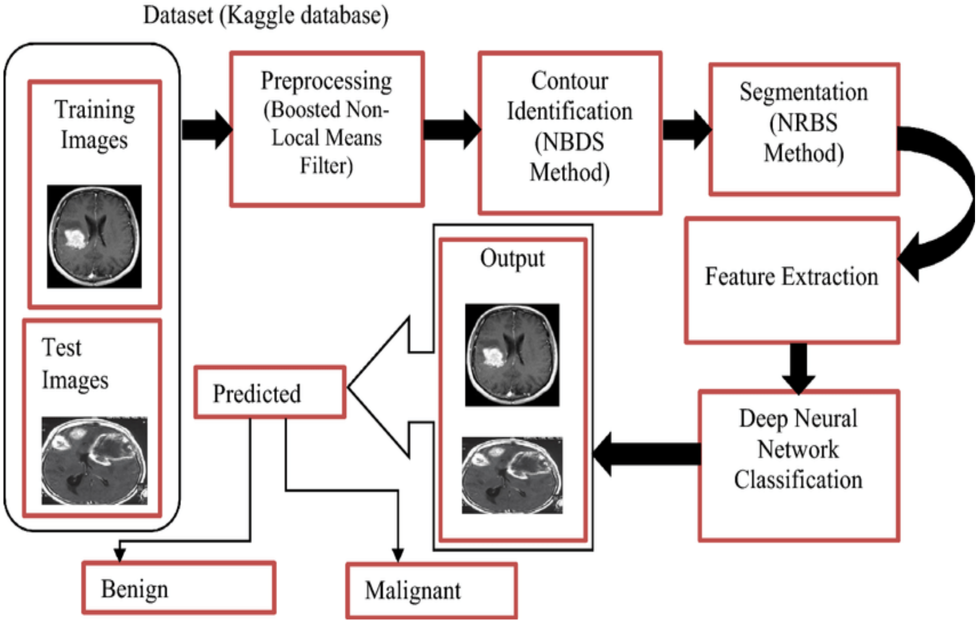

Fig3. The MRI image processing methods contains the below methods. using the images from Kaggle.

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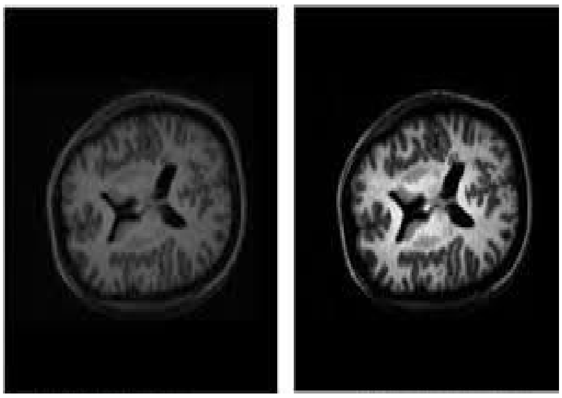
2.1 Preprocessing :

As we discussed the method in the above processing techniques this is the first method in the image processing. The purpose of pre-processing is to raise the image's quality so that we can analyze the image more effectively.



(a) **(b)**

Fig. 4

The one in the left side shows the original image of the MRI scan and the image in the right side is the enhanced image of the MRI scan.[2] Image augmentation to enhance the contrast of the MR brain image and denoising technique to degrade the noise appeared in the MRI images. This method uses a modified non-local resource (NLM) filter. Adaptive window size (MNLM-AW) on grayscale intensity difference (GID), graphics processor (GPU). The transformation between traditional NLM and the proposed MNLM-AW algorithm has different search window sizes (SWS). It degrades noise.

2.2 Segmentation:

The MRI image is divided into multiple parts so studying and analyzing of the image can be improved.

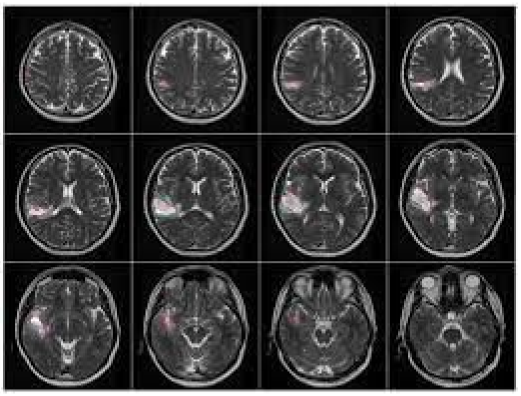


Fig. 5 The segmentation of the MRI image

Tumor detection and segmentation is a key and time-consuming task in medical image processing due to the high variability of brain tumor localization. size and shape. Accurate detection of the size and localization of the tumor in the brain plays an important role in the diagnosis of brain tumor. Cellular neural network or cellular nonlinear network is used as a segmentation tool introduced by Duraiswamy and jane. [3]when all the cells of a cellular neural network are in the linear region, pattern formation, morphology and synergetics can be presented, even though each cell has only first-order dynamics. Convolutional neural networks have been widely used in various tasks. CNN is a method used in medical image segmentation. Recent CNNs are three-dimensional kernels that allow full access to the three-dimensional structure of a medical image. The main disadvantage is the lack of defined data, a large memory of three-dimensional images.

Edge detection is a technique in segmentation that solves image segmentation by detecting edges or pixels in different regions and connected to form closed object boundaries.[4] The boundary approach is the most commonly used segmentation method. It is a gray valve remapping method. Regional approach, which is a regional approach assuming that bounded pixels in the region have the same values. It compares a pixel to its neighbor, and if the congruence criteria are met, the pixels can be set to belong to clusters like one or more of its neighbors.

We can use Kaggle images to train a model to detect a brain tumor on a scanned image, the approximate accuracy would be 97%.

[5]Segmentation methods, including supervised techniques such as thresholding, soft computing, atlas-based, Neural Networks (NNs), and clustering, are employed for tumor segmentation. In the realm of traditional machine learning for tumor segmentation from MRI scans, methodologies predating deep learning are prevalent. These approaches rely on handcrafted features and classical machine learning algorithms. Notable traditional methods include:

1. Support Vector Machines (SVM):

Application: Tumor segmentation using engineered features extracted from MRI images, encompassing intensity-based statistics, texture features, or shape-based descriptors.

2. Random Forests and Decision Trees:

Application: Utilization for segmentation tasks through the construction of decision trees based on image features, facilitating the classification of tumor and non-tumor regions.

3. K-Means and Clustering Algorithms:

Application: Application of unsupervised learning techniques, like K-Means clustering, for segmenting brain tumors by clustering similar regions within MRI images based on intensity values.

4. Graph-Cut Algorithms:

Application: Leveraging graph-based methods such as graph cuts for segmentation. This involves modeling the image as a graph and optimizing a cost function to partition the image into tumor and non-tumor regions.

5. Active Contour Models (Snake):

Application: Deployment of active contour models, also known as snakes, which utilize energy minimization principles to iteratively deform a contour and delineate tumor boundaries on MRI slices.

6. Region Growing and Thresholding:

Application: Utilization of predefined thresholds or seed points in region growing and thresholding techniques to iteratively grow regions in the image based on similarity criteria, thereby segmenting tumors based on intensity or texture properties.

In todays deep learning, advancements in tumor segmentation, particularly in MRI scans, have been achieved. This involves the automatic learning of patterns and features from raw data, significantly enhancing accuracy and efficiency. Various deep learning architectures and methodologies include:

1.Convolutional Neural Networks (CNN):

Usage: Integration into tumor segmentation tasks with architectures such as U-Net, FCN and variants that show remarkable performance. U-Net with its encoder-decoder structure is remarkable for capturing both local and global functions.

2. 3D convolutional neural networks:

Application: Utilizing 3D CNN architectures to process MRI scans as 3D volumes, preserving spatial information across different slices and helping to better understand the 3D structure of a tumor.

3.Mechanisms of attention:

Application: Adapting attention mechanisms, similar to those in Transformer models, to medical image segmentation tasks. These mechanisms allow the networks to focus on relevant regions, thereby increasing the accuracy of tumor segmentation.

4. Generative Adversarial Networks (GAN):

Application: Survey of GANs and their variants for tumor segmentation tasks, where the generator learns to segment tumors while the discriminator provides feedback, leading to improved segmentation results.

5. Ensemble and multilevel approaches:

Applications: Using ensemble methods, combining predictions from multiple models and multi-level architectures that process images at different resolutions to increase segmentation accuracy and robustness.

6. Transfer learning and pretraining models:

Applications: Adopting transfer learning, leveraging pre-trained models on large datasets such as ImageNet and fine-tuning them on medical images, this has proven useful in cases with limited labeled medical data.

2.3 Classification:

Classification of brain tumors is a significant task, and it is essential to carefully extract and select relevant features to achieve accurate results, especially when dealing with numerous MRI images from different cases with known outcomes for training. The primary goal of brain tumor classification is to determine whether the tumor is benign or malignant, and in some cases to assign a specific grade to the tumor based on information obtained from MRI images. Various methods can be used for this classification, including supervised techniques such as KNN, SVM, and ANN, or unsupervised techniques such as FCM and SOM.

Simple classification techniques:

i. Smart Line Drawing with SVM:

Imagine drawing a smart line that separates healthy and possibly tumor-affected areas of the brain. This is what Support Vector Machines (SVM) do.

ii. Automatic pattern recognition with CNN:

Think of convolutional neural networks (CNNs) as glasses that automatically recognize patterns in MRI scans and help detect areas that may have tumors.

iii. Group Decision Making with Random Forests

Random forests act as a group of friends who make decisions together. They consider many factors to decide whether an area looks more like a healthy brain or an area with a possible tumor.

iv. Neighborhood counseling with KNN

K-Nearest Neighbors (KNN) is like asking neighborhood examples for advice. It decides whether a part of the brain is a healthy or possibly a tumor-affected area based on its nearest neighbors.

v. Teamwork with Ensemble Learning

Learning in an ensemble is like getting opinions from different friends. By combining predictions from different classifiers, it provides a more accurate classification of brain tumors.

vi. Intelligent detective work with deep learning

Deep learning models such as recurrent neural networks (RNNs) are like detectives, exploring complex relationships in MRI scans to understand more about brain tumors.

Choosing the right method depends on factors such as the amount of data, the complexity of the task, and the available computing resources. Combining different methods or using their strengths helps to improve the classification of brain tumors and increase its credibility. The figure below shows a deep learning classifier. Fig 3.

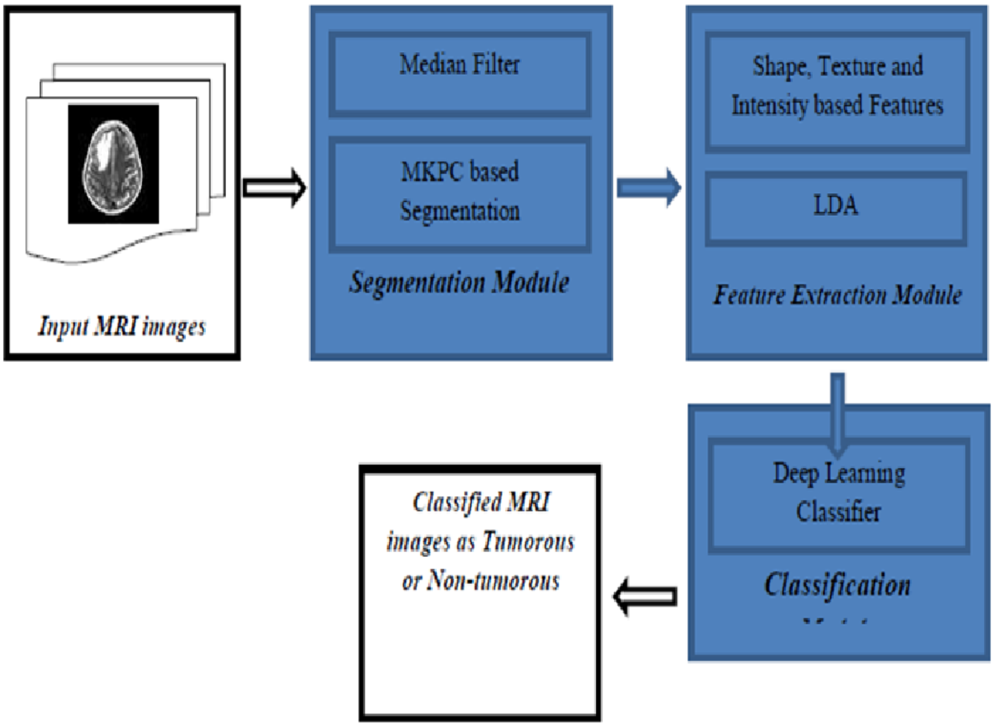


Fig 6 shows the deep learning classification.

2.4 Optimization:

Optimizing the process of brain tumor image recognition through MRI scans encompasses various elements focused on enhancing the precision, effectiveness, and dependability of tumor detection and segmentation. An integral part of this optimization is the significant role that feature extraction plays in the identification of brain tumors using MRI scans.

2.5 Feature extraction:

[6]Representing an image requires a very large dataset, which consumes a large amount of memory and time. To reduce the amount of memory, data and time, features are extracted from the image. Extracted images contain information about the image. Which can be used for image classification and segmentation.

[7]Extracting features from MRI images utilizes different approaches, such as 1) Independent Component Analysis, 2) Fourier Transform, and 3) Wavelet Transform. Fourier transform is deployed to scrutinize the frequency components within an image, whereas wavelet transform is applied for a thorough examination spanning time, space, and frequency domains. In an extensive review of contemporary methodologies for MRI brain tissue segmentation, feature extraction, and classification, these techniques assume a pivotal role.

3. CONCLUSION

Barin tumor detection, segmentation and classification are processes used to produce computer-aided methods for diagnosing tumors from MRI images. These methods provide accuracy and reduced noise. MRI image processing helps doctors in the correct diagnosis of patients. The MRI images that are processed are combined, which helps read the images to detect and classify brain tumors. By doing this we saw that we can take input images from kaggle to train a detection model.

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